© 2026 IJRTI | Volume 11, Issue 4 April 2026 | ISSN: 2456-3315

AI-Powered Personalized Skincare System

Dr. Naadem Divya[1], B. Sai Anjanna Reddy[2], M. Parthu[3], C. Yogitha[4]

[1]Professor-CSE(DS), [2]Department of CSE(DS), [3]Department of CSE(DS), [4]Department of CSE(DS)

Sreenidhi Institute of Science and Technology
Hyderabad, India

[1]divya.n@sreenidhi.edu.in [2]22311A6703@sreenidhi.edu.in
[3]22311A6720@sreenidhi.edu.in, [4]22311A6734@sreenidhi.edu.in

Abstract

This project presents an AI-Powered Personalized Skincare System designed to automate the detection and management of common skin issues using Deep Learning techniques. The system utilizes a Convolutional Neural Network (CNN) model built with the Keras framework to classify facial images uploaded by users into five categories: acne, blackheads, dark spots, pores, and wrinkles. The uploaded images are preprocessed through resizing and normalization before being passed to the trained CNN model for prediction. Based on the detected skin issue, the system intelligently recommends suitable skincare products, including facewash, moisturizer, sunscreen, and serum along with direct e-commerce purchase links for easy accessibility and convenience. The application is developed using the Django web framework and integrates user authentication, a real-time AI chatbot for personalized care advice based on weather conditions, and automated PDF report generation. Performance evaluation using confusion matrix and classification metrics such as Accuracy, Precision, Recall, and F1-Score demonstrates reliable classification. The system is an accessible, cost-effective, and user-friendly alternative to traditional dermatological consultation.

Index Terms

Deep Learning, CNN, Image Classification, Skincare Recommendation, Django, Healthcare

I. INTRODUCTION

Skin health plays a significant role in an individual's overall well-being. Skin-related issues such as acne, blackheads, dark spots, enlarged pores, and wrinkles have become increasingly common due to various environmental and lifestyle factors. Pollution, excessive exposure to ultraviolet (UV) radiation, unhealthy dietary habits, stress, hormonal imbalances, and changing climatic conditions contribute significantly to these problems. Therefore, early detection and proper care are essential to prevent long-term damage and maintain healthy skin.

Traditional dermatological diagnosis is often expensive and time-consuming. Many individuals lack easy access to professional dermatological services and tend to rely on self-diagnosis, which may lead to incorrect treatment and worsening of conditions. With the advancement of artificial intelligence, particularly Deep Learning, automated image-based diagnosis has become a promising solution. Convolutional Neural Networks (CNNs) are highly effective in analyzing visual data and identifying complex patterns in skin images.

The proposed system enables users to upload facial images, automatically detect skin conditions, and receive personalized skincare recommendations. It integrates Deep Learning with web technologies such as Django, along with MySQL for data management, chatbot assistance for interactive guidance, and automated PDF reporting, making it a complete digital skincare solution

A. Background

Skin is the largest organ of the human body and serves as a protective barrier against external environmental factors. Accurate diagnosis of skin conditions is challenging due to variations in lighting, skin tone, and image quality. Convolutional Neural Networks address these challenges by using layers such as convolution, pooling, and fully connected layers to extract meaningful features and classify images effectively, making them suitable for medical imaging applications.

B. Motivation

The motivation behind developing this system arises from the increasing demand for accessible and affordable skincare solutions. Many individuals face difficulties in consulting dermatologists due to financial constraints or geographical limitations. Additionally, misinformation and aggressive product marketing often lead to inappropriate product usage. This project aims to address these challenges by providing:

- Instant AI-based skin condition detection.
- Personalized skincare product recommendations along with direct e-commerce purchase links for easy accessibility.
- Weather-based skincare advice through chatbot assistance.
- A user-friendly web interface accessible anytime and anywhere.

By combining Deep Learning with web technologies, the system empowers users to make informed skincare decisions and reduces dependency on trial-and-error methods.

C. Problem Statement

Despite advancements in healthcare, dermatological services remain inaccessible to a large population. Traditional diagnostic methods rely heavily on manual examination, which can be subjective and inconsistent. Conventional machine learning techniques depend on handcrafted features such as color histograms and texture descriptors, which may fail under diverse environmental conditions. The key challenges include:

- Limited accessibility to professional dermatological consultation.
- High cost and time consumption of manual diagnosis.
- Risk of incorrect self-diagnosis and improper product usage.
- Lack of integrated systems that combine detection, recommendation, and reporting.

These limitations highlight the need for an intelligent, automated, and integrated system capable of accurately classifying skin conditions and providing personalized guidance.

D. Goal of the Project

The primary goal of this project is to develop an AI-driven web-based application that automatically detects common skin issues from facial images and provides personalized skincare recommendations in real time.

E. Objectives

The key objectives of the project are as follows:

- To collect and preprocess labeled skin image datasets for model training.
- To design and train a CNN model capable of classifying five different skin conditions.
- To evaluate model performance using metrics such as Accuracy, Precision, Recall, and F1-Score.
- To integrate the trained model into a Django-based web application.
- To implement secure user authentication using a MySQL database.
- To provide personalized skincare recommendations along with direct e-commerce purchase links.
- To develop an AI chatbot that delivers weather-based skincare advice.
- To generate automated downloadable PDF reports for users.

II. LITERATURE SURVEY

Recent advancements in Deep Learning have significantly improved the performance of automated skin disease classification systems. Researchers have widely explored Convolutional Neural Networks (CNNs) and their advanced variants to achieve high accuracy in medical image analysis. Studies have shown that techniques such as transfer learning, data augmentation, and ensemble models improve classification performance and generalization. Modern architectures like EfficientNet and MobileNet have demonstrated efficiency in real-time applications, while attention mechanisms and explainable AI techniques enhance model interpretability and trust.

Additionally, emerging approaches such as Vision Transformers and federated learning contribute to improved performance and data privacy. Hybrid models combining CNNs with traditional classifiers further enhance decision-making capabilities. Overall, the literature highlights that Deep Learning, particularly CNN-based approaches, plays a crucial role in developing accurate, efficient, and scalable skin disease detection systems.

III. EXISTING METHODS

A. Manual Inspection

Manual visual inspection is the traditional method used for diagnosing skin diseases. In this approach, a dermatolo- gist physically examines the patient’s skin and identifies the condition based on medical knowledge and experience. In some cases, dermoscopy or laboratory tests are conducted for confirmation. This method depends entirely on human expertise and requires in-person consultation.

B. Tele-Dermatology

Tele-dermatology is a remote diagnosis method where pa- tients send images of their skin condition to dermatologists through online platforms. The doctor reviews the images and provides treatment suggestions. Although it reduces physical visits, it still relies on manual human evaluation and profes- sional interpretation.

C. Traditional Machine Learning

Traditional machine learning approaches such as Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Deci- sion Trees, and Random Forest have been used for skin disease classification. These methods require manual feature extraction techniques like texture analysis, color histogram extraction, and edge detection before classification is performed.

D. Rule-Based Systems

Rule-based systems use predefined medical rules developed by experts to identify skin conditions. The system matches input symptoms with stored rules and produces a diagnosis. These systems do not learn from new data and operate only based on programmed logic.

E. Image Processing Techniques

Earlier methods relied on basic image processing opera- tions such as thresholding, segmentation, filtering, and edge detection to identify abnormal skin regions. These techniques focus mainly on pixel-level analysis rather than deep feature extraction.

IV. DISADVANTAGES OF EXISTING METHODS

Manual visual inspection is time-consuming and expensive, requiring physical consultation. It may not be accessible in rural areas and can be subjective depending on the dermatolo- gist's experience. Tele-dermatology depends on image quality and manual review, which may cause delays. It is not fully automated and may struggle to handle large numbers of cases efficiently. Traditional machine learning techniques require manual feature extraction, which is complex and may not gen- eralize well under different lighting conditions or diverse skin tones. Their accuracy is often lower compared to deep learning models. Rule-based systems are rigid and cannot adapt to new or unseen patterns. They require continuous updates and are not suitable for complex multi-class image classification. Basic image processing techniques are sensitive to noise and lighting variations. They cannot effectively capture complex skin patterns, resulting in limited classification performance.

V. PROPOSED METHODOLOGY

The proposed system implements an AI-Powered Personal- ized Skincare System using a Convolutional Neural Network (CNN) integrated with a Django web application. The method- ology followed in the project is described below.

A. Data Preprocessing

The dataset consists of labeled skin images categorized into five classes: acne, blackheads, dark spots, pores, and wrinkles. The images are resized to 32×32 pixels to ensure uniform input dimensions. Pixel values are normalized by scaling them between 0 and 1 to improve model training efficiency and convergence. The dataset is then divided into training and testing sets for model evaluation.

B. CNN Model

A Sequential CNN model is implemented using Keras. The architecture includes Convolution2D layers for feature extraction, MaxPooling2D layers for down-sampling, a Flatten layer to convert feature maps into a one-dimensional vector, and Dense layers for classification. The final output layer uses the Softmax activation function to classify images into one of the five skin issue categories. The model is compiled using the Adam optimizer and categorical cross-entropy loss function. It is trained for multiple epochs to achieve optimal accuracy. After training, the model structure is saved in JSON format and weights are saved in an H5 file for future prediction. .

C. Real-Time Prediction Module

When a user uploads an image through the Django web interface, the system loads the trained model and preprocesses the uploaded image using the same resizing and normalization steps. The model predicts the skin issue using the argmax function to determine the class with the highest probability.

D. Real-Time Prediction Module with direct e-commerce links

Based on the predicted skin issue, the system maps the result to predefined skincare products including facewash, moisturizer, sunscreen, and serum along with direct purchase links. Each skin condition has specific recommended products stored in the system.

E. Chatbot Integration

The system includes an AI chatbot that interacts with the user. After identifying the skin issue, the chatbot asks about the weather condition (hot, cold, humid, or normal) and provides personalized skincare advice based on both the detected issue and environmental factors.

F. Performance Evaluation

The model performance is evaluated using metrics such as Accuracy, Precision, Recall, and F1-Score. A confusion matrix is generated and visualized to analyze classification performance across all five classes.

G. Advantages Of Proposed System

- Automated Feature Extraction – The CNN automatically learns important image features without manual inter- vention.
- Higher Accuracy – Deep learning provides better clas- sification performance compared to traditional methods.
- Real-Time Prediction – Users receive instant results after uploading an image.
- Personalized Recommendations with direct e-commerce links – The system suggests specific skincare products based on the detected issue along with the purchase links.
- Weather-Based Guidance – The chatbot provides environment-specific skincare advice.
- User-Friendly Interface – The Django web application ensures easy accessibility.
- Secure Authentication – User data is stored securely using a database system.
- Automated Report Generation – The system generates downloadable PDF reports for user reference.

VI. SYSTEM DESIGN

This diagram shows the overall architecture. The user in- teracts with the Django web interface, which connects to au- thentication, CNN prediction module, recommendation engine, chatbot, database, and PDF report generator.

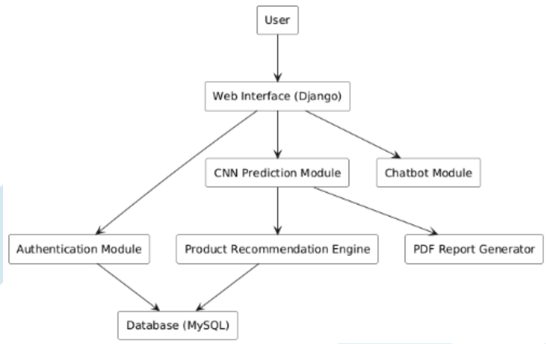

Fig. 1. System Architecture

The user performs actions like login, upload image, get prediction, receive recommendations with direct e-commerce links, interact with chatbot, and download report. [Fig. 2]

Fig. 2. Use Case Diagram

This picture shows every step the system takes, moving from grabbing an image to producing the last result. Right at the start, someone adds a face photo using the website screen; that image travels next into a cleanup stage. In there, adjustments happen - like changing size and balancing light - to get it ready for inspection. Once cleaned up, the image moves forward into a pre-learned CNN setup. Inside this network, key details pop out and a guess forms about what skin issue might be present. When predictions finish, suggestions pop up - customized for your skin concern. Each pick lines up items like cleanser, lotion, sunblock, or treatment drops. Links sit nearby, letting you buy straight through online shops. Over time, everything gets saved - the answers, the details - all tucked into storage for later checks. What shows today might shift tomorrow, based on what came before. A full summary appears at last, laying out the skin issue found and what care steps to follow, ready for download. Step by step, things move cleanly - data flows without hiccups, guesses land fast, every piece links up tight, just like Fig. 3 shows.

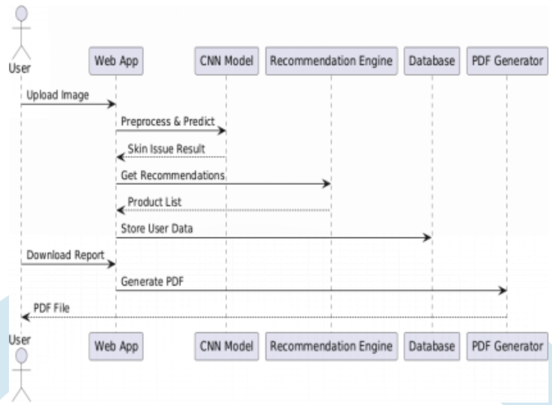

Fig. 3. Sequence Diagram

This diagram represents the workflow of the system from login to prediction and report generation. [Fig. 4]

The class diagram shows system structure. The User interacts with CNNModel, Chatbot, ReportGenerator, and Database. The CNNModel connects to the Recommendatio- nEngine to provide skincare products. [Fig. 5]

VII. Software Requirements

The software requirements for the AI-Powered Personalized Skincare System define the essential technologies and tools required for developing, deploying, and maintaining the application efficiently. These components ensure smooth integration between the deep learning model, web application, and database, while also supporting scalability, performance, and reliability of the system.

A. Operating System

The system is designed to operate on Windows 10 or later versions, providing a stable environment for development and execution. In addition, it is compatible with Linux and macOS platforms, making it flexible for deployment across different operating systems. This cross-platform compatibility allows developers and users to run the application without significant modifications, ensuring wider accessibility.

B. Programming Language

Python is used as the primary programming language due to its simplicity, readability, and extensive support for machine learning and web development libraries. It enables efficient implementation of deep learning models, backend logic, and system integration. Python’s large ecosystem of libraries and frameworks significantly reduces development time and enhances productivity.

C. Web Framework

The Django framework is utilized to develop the web-based interface of the system. It provides a robust structure for handling HTTP requests, managing URLs, and integrating frontend and backend components. Django also includes built-in features for user authentication, session management, and security, ensuring that the application remains reliable and secure.

D. Deep Learning Libraries

TensorFlow and Keras are employed for designing, training, and deploying the Convolutional Neural Network (CNN) model. These libraries offer high-level APIs that simplify model development while providing powerful tools for handling complex computations. They enable efficient feature extraction and accurate classification of skin conditions from facial images.

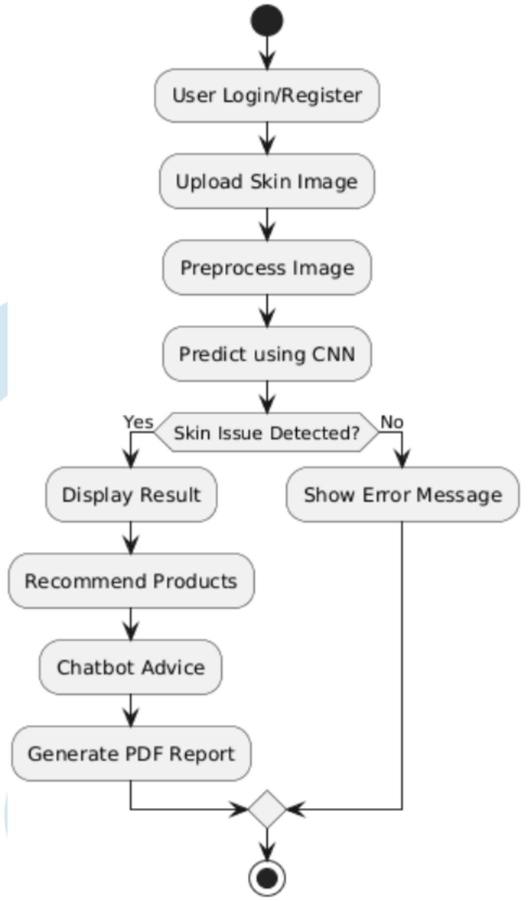

Fig. 4. Activity Diagram

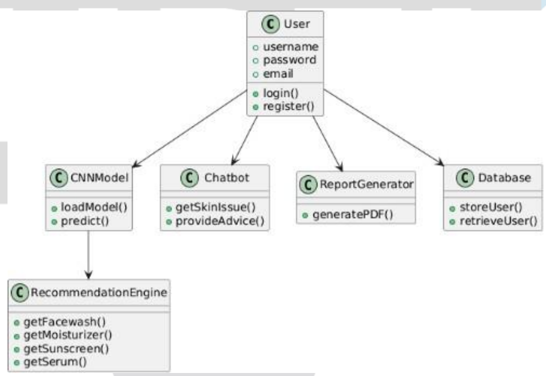

Fig. 5. Class Diagram

E. Database

MySQL is used as the database management system to store user-related information securely. It maintains data such as user credentials, login details, and prediction history. The database ensures data consistency, supports efficient querying, and provides reliable data storage for long-term usage.

F. Frontend Technologies

HTML, CSS, and Bootstrap are used to design the user interface of the application. HTML provides the structure, CSS enhances visual styling, and Bootstrap ensures responsiveness across different devices. These technologies contribute to creating an intuitive and user-friendly interface that improves overall user experience.

G. Development Tools

Development and testing of the system can be carried out using integrated development environments such as Visual Studio Code or PyCharm. These tools offer features like debugging, code completion, and version control support. MySQL Workbench is used for managing the database, while Anaconda or pip is used to install and manage required Python libraries and dependencies efficiently.

H. Supporting Libraries

Several supporting libraries are used to enhance system functionality. NumPy is utilized for efficient numerical computations and array operations. OpenCV is used for image processing tasks such as resizing and normalization. Matplotlib and Seaborn are employed for visualizing model performance and plotting confusion matrices. ReportLab is used to generate automated PDF reports containing prediction results and skincare recommendations for users.

VIII. Hardware Requirement

The hardware requirements for developing and running the system are listed below:

A. Minimum Hardware Requirements

- Processor: Intel i3 or above
- RAM: 4 GB minimum (8 GB recommended)
- Hard Disk: 500 GB
- Display: Standard monitor

B. Recommended Hardware Requirements

- Processor: Intel i5/i7 or equivalent
- RAM: 8 GB or higher
- Storage: SSD recommended for faster performance
- GPU: Optional NVIDIA GPU for faster deep learning model training

IX. Results

The performance of the proposed AI-Powered Personalized Skincare System is evaluated based on the functionality of the developed web application and the effectiveness of the CNN model in classifying skin conditions. The system successfully provides real-time predictions, personalized recommendations, and an interactive user experience.

A. Home Page Interface

The home page serves as the entry point of the system, providing an overview of features such as AI-based detection and skincare recommendations. It allows users to navigate to login or registration pages.

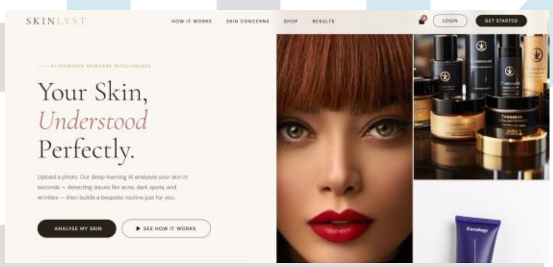

Fig. 6. Home Page Interface

B. User Registration Interface

Starting off fresh, signing up feels light and straightforward thanks to a thoughtfully built entry point for newcomers. Filling in key info like name, passcode, phone, email, plus location gets things moving - no extra steps needed. Instead of clutter, there's space, order, and obvious spots to type what's required. Confusion rarely shows up since each part guides you just enough, nothing more. Even first-time visitors move through it fast, mostly because everything sits where it should. Right off the bat, wrong entries get caught before they cause trouble. Instead of just failing silently, the setup pushes back with clear signs when something is off. Picture a typo in an address - now it gets flagged right away. Stronger passwords? They are gently pushed through guidance, not force. Messages pop up at just the right time, like quiet hints from someone who knows the ropes. Each step feels smoother because feedback fits naturally into the flow. No confusion lingers too long since help shows up exactly where needed.

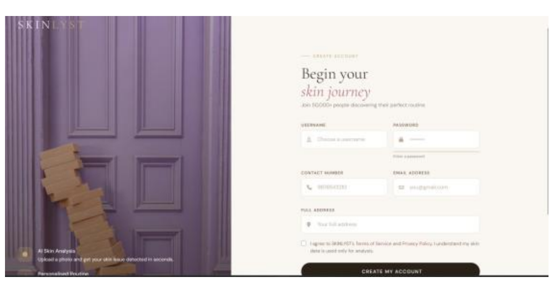

Fig. 7. User Registration Interface

C. Product Recommendation and E-Commerce Interface

The image upload interface makes it easy for users to submit facial images for analysis. With a simple and user-friendly design, users can either upload an image or take a photo directly. It also provides useful guidelines to help users upload clear images for better prediction results.

Fig. 8. Product Recommendation and E-Commerce Interface

D. Image Upload and Skin Analysis Interface

The image upload interface is designed to provide a smooth, intuitive, and user-friendly experience for users to submit facial images for skin condition analysis. The interface features a clean and well-organized layout that minimizes complexity, ensuring that users can easily navigate and interact with the system without requiring any technical expertise. Users are given the flexibility to either upload an existing image from their device or capture a new photo directly using the system, making the process convenient and accessible across different user preferences and devices.

E. Prediction Results

From the start, pixels shift into place when someone uploads a face photo. Resizing comes first - then normalizing colors so they match how the model learned before. A deep learning setup built on layered filters takes over once adjustments finish. Features like roughness or smoothness stand out during scanning by design. Classification follows based on what the network spotted earlier. One outcome gets picked: acne maybe, or blackheads, perhaps dark areas, open pores, or lines etched by time. Decisions form without guessing because patterns guide every call made.

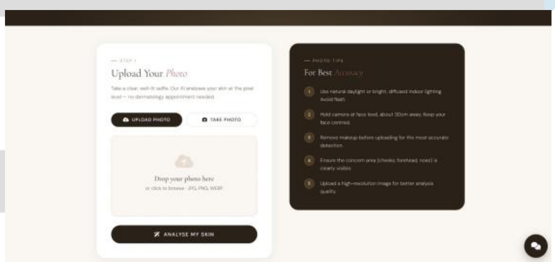

Fig. 9. Home Page Interface

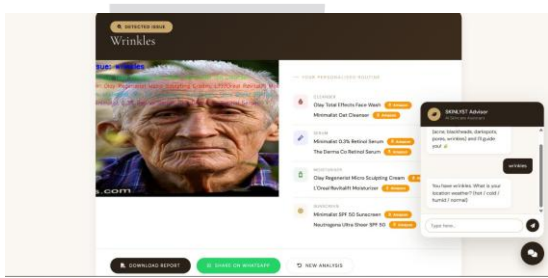

Fig. 10. Prediction Results

F. Performance Evaluation

The performance of the proposed model is evaluated using standard classification metrics, including Accuracy, Precision, Recall, and F1-score. In addition, a confusion matrix is generated to provide a detailed analysis of the model's performance across different skin condition categories.The model achieved an accuracy of 89%, with a precision of 87%, recall of 85%, and an F1-score of 86%. These results indicate that the CNN model is capable of delivering reliable and efficient classification of skin conditions.

X. Conclusion

The AI-Powered Personalized Skincare System successfully demonstrates the application of Deep Learning techniques for automated skin issue detection and recommendation. The system integrates a Convolutional Neural Network (CNN) model with a Django-based web application to provide real- time classification of skin conditions such as acne, blackheads, dark spots, pores, and wrinkles. The use of CNN enables automatic feature extraction, reducing dependency on manual image processing techniques and improving classification accuracy. The system not only detects the skin issue but also provides personalized product recommendations along with direct e-commerce purchase links which includs facewash, moisturizer, sunscreen, and serum. Additionally, the chatbot module enhances user interaction by offering weather- based skincare advice, making the system more intelligent and user-centric. The inclusion of secure authentication and database storage ensures data management and reliability. Performance evaluation using Accuracy, Precision, Recall, F1- Score, and Confusion Matrix confirms the effectiveness of the proposed model. Compared to traditional machine learning and manual diagnosis methods, the proposed system provides faster, automated, and scalable solutions. Overall, the project demonstrates how Artificial Intelligence can be effectively used in dermatological assistance and personalized skincare guidance. The system can be further enhanced by increasing dataset size, integrating mobile application support, and incorporating real-time camera-based detection for improved usability and accessibility.

References

[1] A. Esteva et al., “Dermatologist-level classification of skin cancer with deep neural networks,” Nature, vol. 542, no. 7639, pp. 115–118.
[2] P. Tschandl, C. Rosendahl, and H. Kittler, “The HAM10000 dataset for pigmented skin lesions,” Scientific Data, vol. 5.
[3] N. Codella et al., “Skin lesion analysis toward melanoma detection,” IEEE Journal of Biomedical and Health Informatics.
[4] F. Yu et al., “Automated melanoma recognition using deep convolutional neural networks,” IEEE Transactions on Medical Imaging.
[5] A. Brinker et al., “Deep neural networks are superior to dermatologists in melanoma image classification,” European Journal of Cancer.Informatics.
[6] G. Argenziano et al., “Interactive atlas of dermoscopy,” Journal of the American Academy of Dermatology.
[7] T. Kawahara et al., “Seven-point checklist and CNN-based skin lesion classification,” IEEE Access.
[8] M. Combalia et al., “BCN20000 dataset: Dermoscopic images for skin lesion classification,” Journal of Clinical Medicine.
[9] H. Li and Y. Shen, “Skin lesion analysis using ensemble deep learning methods,” IEEE Access.
[10] S. Han et al., “Classification of the clinical images for benign and malignant cutaneous tumors,” Journal of Investigative Dermatology.
[11] J. Kawahara et al., “Deep features to classify skin lesions,” IEEE International Symposium on Biomedical Imaging.
[12] Y. Fujisawa et al., “Deep-learning-based classification of skin tumors,” Annals of Oncology.
[13] A. Mahbod et al., “Transfer learning using multi-scale deep features for skin lesion classification,” Computer Methods and Programs in Biomedicine.
[14] M. Hekler et al., “Pathologist-level classification of histopathological melanoma images,” European Journal of Cancer.
[15] Z. Yu et al., “Automated skin disease diagnosis using deep learning,” IEEE Transactions on Biomedical Engineering.
[16] R. Dorj et al., “The skin cancer classification using deep convolutional neural network,” Multimedia Tools and Applications.
[17] X. Zhang et al., “Skin disease classification based on deep learning,” IEEE Access.
[18] K. Yasaka et al., “Deep learning with CNN for skin disease classifica- tion,” Radiology: Artificial Intelligence.Informatics.
[19] S. Shrestha et al., “Deep learning for automated skin disease detection,” IEEE International Conference on Healthcare Informatics.
[20] V. Singh et al., “Skin lesion segmentation and classification using deep learning,” Biomedical Signal Processing and Control.
[21] J. Albahar, “Skin lesion classification using CNN with data augmenta- tion,” IEEE Access.
[22] R. Hasan et al., “Hybrid deep learning approach for skin disease recognition,” Sensors.
[23] L. Perez and J. Wang, “The effectiveness of data augmentation in image classification,” arXiv.
[24] K. He et al., “Deep residual learning for image recognition,” Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR).
[25] A. Krizhevsky et al., “ImageNet classification with deep convolutional neural networks,” Communications of the ACM.